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Sensor fault detection and diagnosis based on bilinear mass balances in wastewater treatment systems

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Abstract. With this paper we adapt the fundamental framework of data reconciliation for bilinear steady-state systems to solve the problem of fault detection and diagnosis in the context of full-scale wastewater treatment plants (WWTPs). The usefulness of this framework is illustrated using the BSM1_LT simulation platform to detect and identify faults in flow and TSS sensors. The results show that data reconciliation of bilinear systems is a powerful method to detect faults in the flow measurements but exhibits low performance for faults in the TSS sensors for the given sensor configuration.

Key words: Data reconciliation, bilinear balance equations, fault detection and identification

1. Introduction

Until the late nineties, sensors were seen as the main obstacle to introducing reliable process control in wastewater treatment. Nowadays, sensors have been developed to the extent that their nominal specifications permit automatic control of sludge age and carbon, nitrogen and phosphorus removal processes (Vanrolleghem and Lee, 2003; Olsson, 2012). However, the quality of the resulting measurements is not always assured at all times. Several problems can occur which influence the quality of the signal negatively. Furthermore, the symptomatic effects of sensor faults on the measurements that are included in control loops can be hidden because of dampening by feedback control. A systematic approach to fault detection and identification (FDI) is therefore welcome.

Figure 1 illustrates that the effect of a failure in one of the sensors involved in the SRT calculation can be dramatic. In this case, TN in the effluent and the concentration of the nitrifying biomass of an activated sludge system using SRT control is shown for two types of situations, 1) no faults in the sensors and 2) a TSS sensor bias for the wastage flow (X_{WAS}) on day 400. The total nitrogen concentration in the effluent increases up to 25 g·m^3 because the nitrifying biomass is washed-out from the system due to the combined effect of winter time and X_{WAS} measurement fault. The system recovers slowly in the summer period (day 520). Despite obvious effects on performance, visual inspection of the X_{WAS} measurements (not shown) does not lead directly to the root cause.

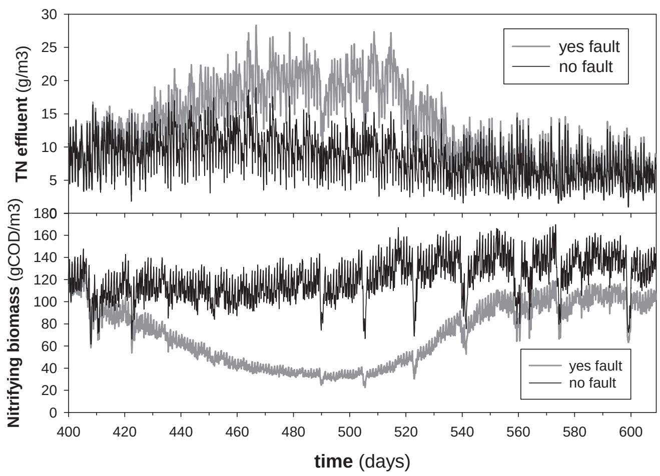

Figure 1. Influence of a fault in the TSS wastage sensor on the TN in the effluent and on the nitrifying biomass concentration in a plant using SRT control at 10 days

The above motivating example suggests that sensor inspection based on normal ranges of values may not be sufficient for proper detection and identification of faults. For this reason, we adapt a framework based on linear and bilinear balance equations which enables to detect faults in both flow rate and TSS measurements. If the mass balance does not close with the available measurements a fault might be occurring in one of the sensors involved in the calculation of the mass balance. The framework is well established, general and popularly used in chemical engineering for data reconciliation, fault detection and identification (FDI) and optimization of sensor locations (Crowe et al., 1983; Crowe, 1986). In the wastewater community, several methods have been presented. In Puig et al. (2008), mass balancing based on phosphorus measurements is pursued. Importantly, the provided method assumes a steady-state and does not allow for balances to be considered over unit processes with temporary accumulation of soluble compounds or for reactions. In Spindler and Vanrolleghem (2012) a similar theoretical basis is used. In this case however, a CUSUM chart enables to attenuate temporary imbalances because of its integrating property. In contrast, a general method which accounts explicitly for temporary imbalances (because of reactive or accumulating unit processes) is applied in this work.

To illustrate the usefulness of the method, three faulty scenarios are tailored introducing faults in sensors which are known to be redundant, after applying the structural observability and redundancy analysis presented by Villez et al. (2013).

2 Method

2.1 Simulated system and fault scenarios

The simulation platform used is the Long-Term Benchmark Simulation Model (BSM1_LT) (Rosen *et al.*, 2004), which was developed with the specific objective of objective evaluation of process monitoring, fault diagnosis and automation strategies. In Corominas *et al.* (2011) this platform was extended with a procedure for objective evaluation of monitoring performance. For this case study, the Sludge Retention Time (SRT) of the system was controlled at 10 days by means of a PI controller which manipulates the internal recycle flow rate of the plant. The implementation of the faults is largely based on the approach described in Rosen *et al.* (2004) and adapted in Corominas *et al.* (2011). A bias of 25% has been applied to the different sensors when faults are activated.

The simulation protocol for BSM1_LT is as follows: First, the model is run to steady state for 200 days using a constant influent, without any faults. Afterwards, a dynamic simulation is conducted using dynamic influent data (flows, concentrations and temperature) for a period of 609 days at 15 minute interval. At day 400 the faults are applied and remain active until the end of the simulation, i.e. no corrective action is taken. For each scenario, the method is applied to the data obtained from day 401 to 600. Simulations are conducted with Matlab and output data is stored every 15 minutes.

Table 1. Simulated fault scenarios

Identifier	Sensor symbol	Sensor affected by fault	Type and magnitude of fault
Scenario 0	-	none	None
Scenario 1	Q_{WAS}	Flow in the waste flow	Bias 25%
Scenario 2	X_{WAS}	TSS in the waste flow	Bias 25%
Scenario 3	X_{AER}	TSS in the aerobic reactor	Bias 25%

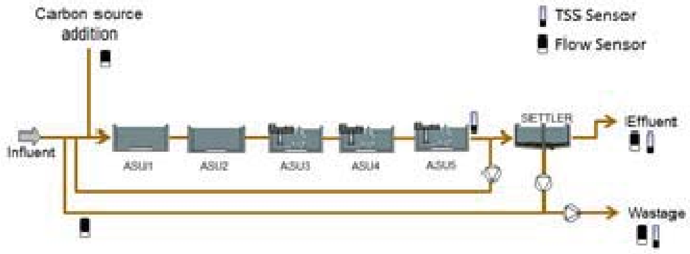

Figure 2: BSM_LT plant scheme with flow and TSS sensors as icons.

Flow sensors are placed in five locations (see Figure 2): (1) influent flow (Q_{IN}), (2) carbon dosage flow (Q_{CARBON}), (3) sludge recycle flow (Q_{RAS}), (4) sludge waste flow (Q_{WAS}) and, (5) effluent flow (Q_{EFF}). TSS measurements are placed in three locations: the aerobic reactor exit flow (X_{AER}), the sludge waste flow (X_{WAS}) and, the effluent flow (X_{EFF}). For this configuration, one can establish that all flow sensors except the sludge recycle flow (Q_{RAS}) are structurally redundant (Villez et al., 2013). The chosen fault scenarios summarized in Table 1 exclude faults in sensors which are not structurally redundant and could therefore never be detected.

2.2 FDI framework for bilinear systems

The applied general framework for Fault Detection and Identification is based on the formulation of data reconciliation tasks as a Non-Linear Program (NLP). In contrast to linearization approaches as in Crowe *et al.* (1983), the problem is solved directly by means of deterministic global optimization techniques. Of particular importance is the appearance of bilinear terms in the mass balances based on flow rates and concentrations. For this reason, the chosen optimization scheme is based on a branch-and-bound algorithm for which the lower bounds are based on so called McCormick relaxations (McCormick, 1976). The objective function of the mathematical problem is defined as the Weighted Sum of Squared Residuals (WSSR), which measures the distance between the vector of reconciled measurements and the original, noisy measurements. Detailed procedures will be detailed in a forthcoming publication.

3. Results and conclusions

Figure 2 shows the WSSR for days 401 until 600 for each scenario. The 90% confidence limit is defined as the 90% quantile for the WSSR values in the days 401 to 500 in the normal scenario (Figure 2, scenario 0). The subsequent 100 days are used for testing. To this end, any WSSR value which is higher than the set 90% confidence limit is said to produce an alarm. Since no true fault is present, any alarm is a false alarm. As such, 15 false alarms are produced. In other words, a 15% false alarm rate (also: false positive rate) is observed which is higher than expected. Fault detection results are good for scenario 1 where on 80% of the days an alarm is given (80% true positive rate). Results are not as good for scenarios 2 and 3 with 14.5% and 30% as true positive rates. At this stage it is unclear whether this is (1) due to noise, (2) the particular plant and sensor configuration or (3) inherent difficulties of the method to detect faults in concentration variables such as TSS. In this contribution, we present fault detection and identification (FDI) results obtained with a framework for data reconciliation for bilinear systems which is based on global deterministic optimization. We show by means of the BSM_LT platform that the framework works fine for detection of bias faults in flow rates (scenario 1) but shows low performance for bias faults in TSS measurements (scenarios 2 and 3). In the future, the framework will include fault diagnosis as well and provide data reconciliation automatically.

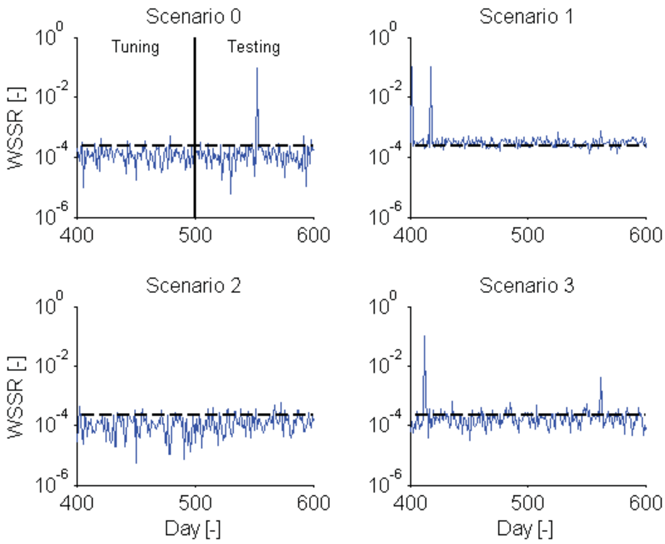

Figure 2. WSSR statistic for 4 scenarios. The horizontal line indicates the 90% confidence limit.

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